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Abstract

In this study, we examine the notions of perceived ease of learning (PEL) and perceived ease of use (PEU) and their impact on the performance of applying the object-oriented methodology (OOM). We propose a research model that stipulates that PEL positively influences PEU and both PEU and PEL are positively related to performance. As expected, we found that PEL was strongly related to PEU. Findings regarding the causality of PEL and PEU on performance were partially supported. To test the hypotheses, we conducted an experiment to collect data from a group of undergraduate students in a large Midwest University. Structural Equation Modeling was employed to analyze the data.

Keywords: Object-oriented analysis, data and process modeling, perceived ease of use and learning, technology acceptance model

Introduction

The growing demands for bigger, better, and more adaptive software have led many scholars and developers to believe that the trend of software design is moving toward more object-orientation. Proponents of the object-oriented methodology (OOM) have stated that the OOM improves the communication between users and analysts, increases productivity and reliability, enhances reusability of code, and reduces the load of code maintenance (Booch, 1991; Yourdon, 1994; Garceau et al., 1993).

In the traditional structured design methodology, a software system is viewed as a collection of data and functions that operate on the data. Thus, in order to obtain a comprehensive model that represents a business problem, the traditional methodology usually employs two different models: an entity-relationship-diagram to represent the data involved in the system and a data flow diagram (DFD) to represent the functions or activities that operate on the data. In contrast, in the OOM, a software system is viewed as a collection of "objects", each of which is a self-contained module encapsulating both data and functionalities. Therefore, in the OOM analysts often employ so-called class diagrams or object models, to capture the structural part of a business problem.

Based on these underlying differences, the shift from traditional methodology to the OOM may not to be straightforward. Booch (1991) and Korson and McGregor (1990) stated that object-oriented methods require a different way of thinking about decomposition. In the same vein, Fichman and Kemerer (1992) pointed out that experienced analysts in traditional systems development would view the OOM as a radical change. This is because the solution to a business problem using the OOM will require to model data and functions in only one structure: an object, which could be a very challenging task for analysts trained in traditional methodologies. There have been studies that examine how these methodology shifts have impact on the performance and perception of systems analysts trained in traditional methodologies. However, existing studies along this line are inconclusive. For example, some found that the OOM was perceived to be very difficult to learn and apply while others found the opposite.

The lack of conclusive results regarding perceived ease of learning (PEL) and perceived of ease of use (PEU) of the OOM is not the only motivation to conduct the current research. Existing studies have also failed to consider prior experience in data modeling, such as the entity-relationship-diagram, to predict performance when applying the OOM. They have mainly considered process model experience, such as the data flow diagram (Morris et al., 1999; Agarwal et al., 1996a, 1996b). Comparing process modeling and class diagramming without data modeling is not a fair comparison between the traditional method and the OOM. Thus, we believe it is important to extend the existing studies by considering prior data modeling experience.

Note that PEU is a construct borrowed from the Technology Acceptance Model (TAM). When defining PEU, Davis (1989) and many other studies consider ease of learning as a sub-dimension of ease of use. For example, in his final list of 6 items for PEU, Davis (1989) uses two of them to tap ease of learning: Easy to Learn and Easy to Become Skillful. We believe that treating PEL to be a component of PEU is reasonable as long as understanding a technology can directly contribute to its ease of use as in the case for most end-user technologies such as email and word processors. However, when dealing with a technology such as a systems development tool or an enterprise application, ease of use and ease of learning may not go along with each other because the understanding of concepts does not automatically translate into a successful application of them. The latter often requires originality, creativity, and the ability of maneuvering concepts for logical induction and deduction. Whether a user is willing to adopt it and how well he or she uses it may depend on how easy it is to learn, or how easy it is to apply, or both. Therefore, we propose to treat ease of learning and ease of use as two distinct constructs as in Lederer et al. (2000).

This study intends to accomplish two objectives. First, the inquiry may lead us to a better understanding about various methodology migration issues and shed some light on the debate between revolutionary vs. evolutionary theories (Liu and Grandon 2001; Morris et al., 1999; Sircar et al., 2001) from a different perspective. Second, this study attempts to determine which belief, PEL or PEU, or both, can better predict performance.

Related Studies

According to the TAM (Davis, 1989; Davis et al., 1989), perceived ease of use and perceived usefulness are proved to influence attitudes toward use, which in turn influence behavior. These two constructs have been widely accepted among the MIS research community and the model has been empirically tested by successive work (e.g. Doll et al., 1998; Gefen and Keil, 1998). Similarly, the theory of reasoned action (Ajzen and Fishbein, 1980) also suggests that attitudes influence behavior, including performance.

There have been many studies examining the ease of use of the OOM. However, their results are inconclusive and even conflicting with each other. Vessey and Conger (1994) and Agarwal et al. (1996b) found that the OOM were more difficult to learn and apply than process-oriented methods within a group of novices. In contrast, Lee and Pennington (1994) found that object-oriented design is easier and faster to learn than procedural design. Most recently, Johnson and Hardgrave (1999) developed a framework to categorizing advantages, disadvantages, social referents, and obstacles associated with the adoption of the OOM based on the theory of planned behavior (Ajzen, 1991). By using 94 experienced object-oriented programmers, they found that the OOM was perceived easier to learn even though the responses had a large variability.

There can exist many explanations to the inclusiveness of the results. First, the measure of ease of use varies from study to study. For example, Boehm-Davis and Ross (1992) use the percentage of project completion; Lee and Pennington (1994) and Vessey and Conger (1994) use qualitative differences in object decompositions and cognitive processes; Johnson and Hardgrave (1999) use perceptions. Second, sampling tends to be biased toward one or another direction in the studies. For example, all the subjects in Johnson and Hardgrave (1999) were experienced object-oriented programmers while those in Vessey and Conger (1994) were novices. Although some studies controlled prior experience of their subjects, they focused on the control of process design or programming experience (e.g., using data flow diagrams and program flow charts) and failed to control the experience in data modeling (e.g., using entity-relationship diagrams).

Note that, although the term “ease of use” is floating over the studies on the OOM, the notion has never been precisely defined or directly measured. It could be interesting to make inquiries on how PEU of the OOM influences one’s performance on object-oriented tasks.

Research Model and Hypotheses

The focus of this study is to bridge a connection between performance and PEU and PEL beliefs in the context of adopting the OOM. In particular, we treat PEU and PEL as two distinct constructs that affect performance. We examine how the two cognitive beliefs are related and which belief, PEL or PEU, is more relevant to the prediction of performance. Figure 1 shows our research model.

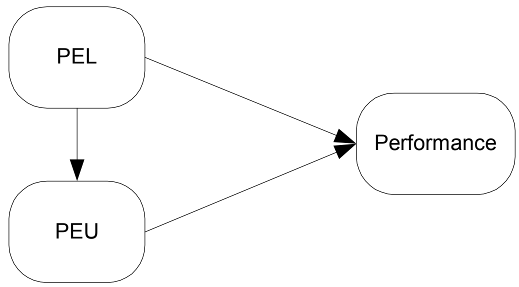

Figure 1. Research Model

Lederer et al. (2000) in an attempt to validate TAM in a Web application environment and to identify antecedents to Web ease of use and usefulness found that ease of understanding played an important role in determining ease of use. We believe that a good understanding of the OOM will contribute to its effective use. Therefore, we anticipate that ease of learning will positively influence ease of use, as speculated by the following hypothesis:

Hypothesis 1: *The perceived ease of learning of the OOM positively influences the perceived ease of use of the OOM.*

The expectancy theory of motivation (Vroom, 1964) gives us a solid theoretical background to connect the notions of PEU and PEL with performance. In general terms, this theory states that a person's motivation to exert effort towards a specific level of performance is based on his/her perceptions of associations between actions and outcomes. In other words, an individual holds a high expectancy about an outcome if and only if he or she feels it is easy to attain the outcome. For example, when goals are set too high or the performance expectations are made too difficult, the expectancy is low and the performance decreases. Applying these notions to the context of object-oriented tasks, we argue that when individuals perceive that the OOM is easy to learn and apply then they will have a high expectation of the outcomes, which in turn, will increase their performance in an object-oriented task. Thus, we hypothesize the following:

***Hypothesis 2**:* *The perceived ease of learning of the OOM has a direct positive impact on the task performance of using the OOM.*

***Hypothesis 3**:* *The perceived ease of use of the OOM has a direct positive impact on the task performance of using the OOM.*

Method

Research Design

To validate the research model and eliminate any bias from the sample selection, we conducted an experiment using the 2 × 2 factorial design, where the two factors are respectively data modeling experience (DME) and process modeling experience (PME). Each factor was controlled at two levels, 0 and 1, which respectively represent the absence and the presence of the corresponding experience. For example, DME = 1 represents that one is experienced in data modeling while DME = 0 represents the opposite. Table 1 shows the design matrix, where Group A consists of subjects experienced in both data and process models; Group B only in data models; Group C only in process models; and Group D consists of all inexperienced subjects, who have no prior exposure in either data modeling or process modeling.

Table 1. 2 × 2 Experiment Design

		PME	
		PME=1	**PME=0**
DME	**DME=1**	A	B
	DME=0	C	D

Subjects and Task

The subjects for the experiment were recruited from a business school at a large Midwest American university. The incentive for participation was toward extra credit points (based on participant's performance) to each subject if he or she agreed to participate in and finished the experiment.

We controlled the level of prior experience according to relevant courses previously taken by the subjects and provide additional training if necessary. A subject was declared to be experienced in data modeling if he or she had received at least five-week intensive classroom instructions on the entity-relationship-diagram in the current semester and had done at least 20 data modeling questions. Similarly, a subject was declared to be experienced in process modeling if he or she had received at least five-week intensive classroom instruction on data flow diagrams in the current semester and had extensive process modeling exercises. On the other hand, a subject was declared to have no experience in data modeling or process modeling if he or she had no prior exposure to such topics.

To implement the design, we requested the rosters of all current and previous Database Management and Systems Analysis classes and screened each subject with respect to his or her prior experience in data modeling or process modeling. Initially, we recruited 5 classes and 223 candidates in total. After the screening, we selected 131 subjects from 4 classes and provided each of them with an 18-page training material on object-oriented modeling using class diagrams two weeks before his or her experiment. The material covered the essential concepts of object-orientation and how to draw class diagrams to model business problems. It also included a list of review questions and exercises that each subject needs to go over and practice. Before the experiment, we administered a 10- minute quiz, which consisted of 5 screening questions. A subject was dropped from the further study if he or she had less than 3 points out of 7 in the quiz. By doing so, we ended up with 115 subjects. Among them, 66 were males and 49 were females.

The same experimental task was given to the four groups of subjects. Agarwal et al. (1996a, 1996b) suggested that some tasks are more process-oriented while some others are more object-oriented depending on the degree of process and structure inherent in the task. Thus, in order to eliminate any bias due to the type of problems, we selected a problem from Post (1999) and modified it to include both process requirements and structural features (see Appendix). We created a "correct" solution as a reference to measure the quality of the solutions produced by each subject.

Dependent Variables and Their Measurements

Performance

We measured the task performance of each subject based on the design quality of his or her solution. We define design quality as the extent to which a model designed by the subject captures all data and functional requirements specified in the problem description and satisfy the goals of the OOM (Liu and Grandon, 2001). We used the concepts of facets (Batra et al. 1990) and modified the grading scheme proposed by Morris et al. (1999). We weighted all facets in the grading system and distinguished major components from minor ones within each facet. A scale varying from 1 to 100 was utilized to score the solutions. We call this grading procedure a *facet-based scheme*. Table 2 shows the grading schema utilized in this study.

Table 2. Facet-Based Grading Scheme

Facets	*Weight*	*Points*	*Weighted Score*
Major Object	30%	100	30
Minor Object	10%	100	10
Services	15%	100	15
Attributes	15%	100	15
Relationships	30%	100	30
TOTAL	*100%*		*100*

Besides using the facet-based grading, we also evaluated each solution according to its overall feel and look. This scheme focuses more on the correctness of using the object-oriented concepts such as inheritance and how close the solution is to the abstract structure of a good design, i.e., the schema, of an expert in object-orientation (Jeffries et al, 1980). We call such a grading system a *schema-based scheme*.

To ensure the reliability of performance measurement, we had two independent experts to evaluate each solution blindly by using both grading schemes. First, each expert used the schema-based scheme to grade the solutions based on a glance of the models and his or her overall feelings of them. Then, a few days later, he or she used the facet-based scheme to grade them based on the five main facets described in Table 2. Finally, the average of the evaluations by each expert was taken as the score for each solution (g1 and g2 in figure 2 below).

PEU-PEL

We use Davis's (1989) definition of PEU: "the degree to which a person believes that using a particular system would be free of effort" (p. 320). Similarly, PEL is defined here, as the degree to which a person believes that learning a particular system would be free of effort. We believe that the effort put into learning and using a system methodology is different in both cases. For example, learning a design methodology would require more effort in understanding and comprehending concepts associated with the method while using the method would require more effort in interacting with the system. Thus, in order to develop a measure for the PEL and PEU of the OOM, we first referred to the 6 items validated by Davis (1989) and others. For instance, we selected four items from the list with no modifications: Easy to Learn, Easy to Become Skillful, Clear and Understandable, and Easy to Use and classified them according to the type of effort involved. For example, we considered Easy to Become Skillful and Ease to Use together and put them into the PEU construct. Similarly, we put Ease to Learn and Clear and Understandable together into the PEL construct. Then, we added more items and classified them according to the effort differences. We finished with 7 items for PEU and 8 items for PEL. However, similar to what Davis (1989) found, successive pilot testing and validating indicated that these items did not correlate with the rest of the items very well in each construct respectively. Therefore, we did not include them all in this study. Finally, we selected 5 items to measure the PEL and 4 items to measure the PEU of the OOM (Table 3). For each item, we used a 7-point Likert scale and asked each subject to provide a response ranging from "strongly disagree" to "strongly agree".

Table 3. Perceived Ease of Learning and Use Measurement

PEL1:	It is easy to comprehend object-oriented concepts
PEL2:	I felt comfortable in studying object-oriented analysis and modeling
PEL3:	The object-oriented concepts seems to be straightforward
PEL4:	I found it difficult to understand object-oriented concepts
PEL5:	It took me too much time to learn object-oriented analysis and modeling
PEU1:	I felt comfortable in applying object-oriented models
PEU2:	Modeling business problems using class diagrams seems to be ease
PEU3:	It is easy to apply the object-oriented analysis and modeling
PEU4:	Applying object-oriented models did not require much of my mental effort

Results

Structural equation analysis was performed using LISREL 8.3. SIMPLIS syntax was coded in order to test both the structural and measurement models. The exogenous latent construct PEL was measured considering 5 items, the endogenous PEU construct used 4 items and the performance endogenous latent variable was measured using 2 items (g1 and g2 raters evaluations).

Overall Model Fit

Many overall measures of data-model fit have been suggested in the literature in an attempt to give the researcher a criterion by which to judge whether or not a particular data set is consistent with an a priori hypothesized model (Josekog and Sorbom, 1989; Kelloway, 1998; Byrne, 1998; Hair, 1998). Therefore, there is no single recommended measure of model fit. In this study the most common measures of data-model fit are presented. Table 4 shows a summary of the findings along with the recommended cut-off values.

Table 4. Indexes for the Overall Model Fit

	Cut-off Value	Obtained Value
Chi-square/DF	<5	53.60/41=1.3
Root Mean Squared Error of Approximation	<.05	.055
Goodness of Fit Index (GFI)	>.90	.92
Adjusted Goodness of Fit Index (AGFI)	>.80	.87

According to Byrne (1998) the first goodness-of-fit statistic to be reported is the Root Mean Square Error of Approximation. This index takes into account the error of approximation in the population. Values less than .05 indicate good fit. We obtained a fairly acceptable value. The Chi-Squared divided by degrees of freedom is 1.3, which is below the cut-off value suggested by Hair et al. (1998), as indicative of fit model. The Goodness of Fit Index is .92, and the Adjusted Goodness of Fit is .87, indicating that our hypothesized model fits the sample data very well (Byrne, 1998; Gefen et al., 2000). Together, these four measures indicate a quite well fit for the overall model. The following figure presents the results from the LISREL analysis.

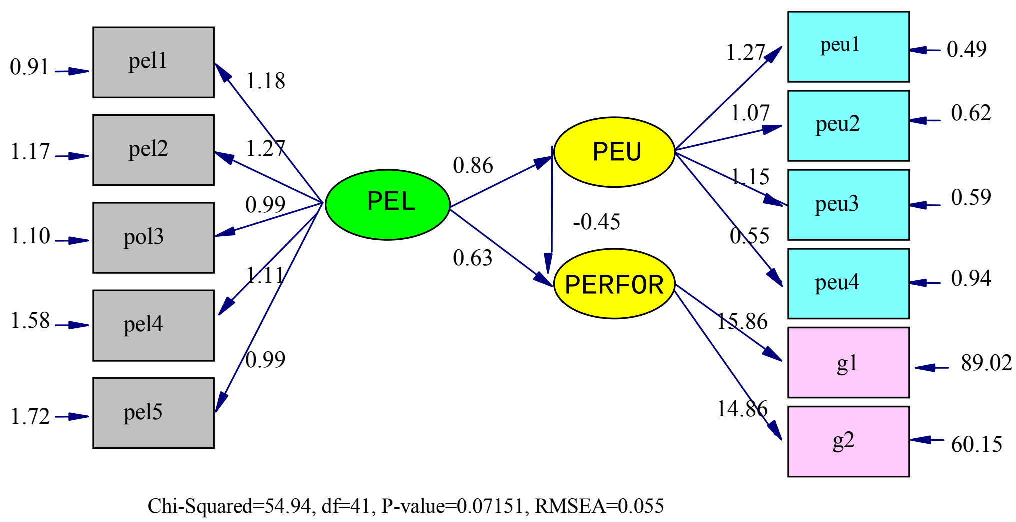

Figure 2. Results from LISREL

Measurement Model

The first step in the analysis of the measurement model fit is an examination of the indicator loadings for statistical significance (Hair et al., 1998). Table 5 shows the loadings for each item along with their corresponding t-values (in parenthesis) and their respective R^2 .

We used the guidelines recommended by Hair et al. (1998) in determining the relative importance and significance of the factor loading of each item. According to their criteria, all the loadings in the measurement model are very significant. Furthermore, for each variable the t-values associated with each of the loadings exceed the critical value for .01 significance level (critical value = 2.576). Moreover, the R^2 of each equation turned to be fairly high. Therefore, all the variables are significantly related to their specific constructs, verifying the posited relationships among observable and latent variables.

The second step in the analysis of the measurement model fit is to determine whether the specified observable variables are sufficient in their representation of the constructs (Hair et al. 1998). Computation of the construct reliability and the variance-extracted measure were performed using the standardized loadings and the measurement errors. Table 6 shows the results of the calculations:

Table 5. Parameters Estimates for the Measurement Model

Items	PEL	PEU	Performance	R^2
PEL1	1.18 (9.32)			0.61
PEL2	1.27 (9.04)			0.58
PEL3	0.99 (7.84)			0.47
PEL4	1.11 (7.51)			0.44
PEL5	0.99 (6.64)			0.36
PEU1		1.27 (6.82)		0.77
PEU2		1.07 (6.54)		0.64
PEU3		1.15 (6.67)		0.69
PEU4		0.55 (4.55)		0.24
G1			15.86 (5.88)	0.74
G2			14.86 (5.82)	0.79

Table 6. Construct Reliability and Variance Extracted

Latent Variable	Construct Reliability	Variance Extracted
PEL	.83	.48
PEU	.86	.6
PERFOR	.86	.75

The three constructs' reliability exceeds the recommended value of .7. For the variance-extracted measure, PEL construct has a value of .48, fairly close to the recommended 50 percent (Fornell and Larker 1981). Performance, with a value of .75 exceeds the recommended value significantly.

Structural Model

The test of the structural model includes the estimation of the path coefficients, which are interpreted as standardized beta weights in a regression analysis. The path coefficient of an exogenous latent variable represents the direct effect of that variable on the endogenous latent variables. As hypothesized (H1), PEL has a direct positive effect on PEU since the loading is very high (.86) and the t-value is significant at .01 level (see table 7 below).

Table7. Parameter Estimates for the Structural Model

	Endogenous Variables		Exogenous Variable
Endogenous Variables	**PEU**	**PERFOR**	**PEL**
PEU	.000	.000	.86 (5.27)
PERFOR	-.45 (-1.57)	.000	.63 (2.02)

Hypotheses 2 and 3 tested whether PEL and PEU of the OOM have a direct positive effect on performance. Performance was found to be positively influenced by PEL but negatively influenced by PEU. An explanation of these findings is offered in the next section.

Conclusion

Inspired by the expectancy theory of Vroom (1964) and the TAM of Davis (1989) we studied how the PEU and PEL correlate to performance. In particular, we proposed the notions of PEL and PEU in the context of the OOM. We also studied how PEL influences PEU. Finally, we related PEL and PEU to performance based on the expectancy theory and investigated how these cognitive beliefs influence the performance in OOM tasks.

Consistent with prior conceptual and empirical research, this study significantly corroborated that the PEL predicts the PEU. This means that those subjects who found the OOM easy to learn found it also easy to use. Thus, our assertion that a good understanding of the OOM will contribute to its effective use is definitely confirmed.

By treating ease of learning and ease of use as two different constructs, in this study we developed a novel theory that explains which belief, PEU or PEL better explain performance when applying the OOM. As was hypothesized (H2), there is a direct positive relationship between PEL and performance, such that, subjects who found the OOM easy to learn had a good performance when solving the task. These results are consistent with the expectancy theory (Vroom 1964). When subjects have a high perception of ease of learning the OOM, their expectancy is also high, and in turn, their performance increases when applying the object-oriented tool.

In contrast to what was hypothesized (H3), participants who found the OOM easy to use performed relatively poor. Considering that PEL predicts PEU and PEL predicts performance (see table 7 above), why PEU does not predict performance? Our explanation lies at how PEL and PEU were measured. Note that, before performing the experimental task, we gave each subject two weeks to study an 18-page material on the OOM. We also designed a quiz to screen the subjects such that those included in this study actually read the material. Therefore, each subject estimated the PEL of the OOM based his or her actual learning experience obtained prior to the experiment. In contrast, the assessment of PEU was highly speculative. All the subjects have no or little experience in applying the OOM to real business problems.

With the above difference being pointed out, our explanation for the paradoxical findings is becoming clear. That is, PEL or PEU determines the task performance of using a technology only if it is assessed and adjusted based on direct experience with the technology. The rational is as follows. When a subject gains more experience with a technology, his or her PEL and PEU will gradually reflect its objective ease of learning and ease of use, which is often considered to determine performance and sometimes even considered to be a synonym to performance (Venkatesh & Davis, 1996). Applying this theory to the context of the current study, we then understand that the significant relationship between PEL and performance (parameter estimate is .63 for the structural model according to table 7) is due to the fact that the measurement of PEL reflected the actual ease of learning of the OOM. Similarly, PEU is insignificant to performance because its estimate was not performance or experience-adjusted.

Our explanation is consistent with existing theoretical and empirical evidence. In order to predict PEU using the objective ease of use, Venkatesh and Davis (1996) proposed the notion of objective usability (OU) that captures the actual level of effort required to complete specific tasks. To further operationalize the concept, they measured OU by the ratio of the expert performance on a task to the subject performance on the same task. A technology was declared objectively easier to use if it had a higher OU estimate. Based on the responses from 76 students, Venkatesh and Davis (1996) found that OU did not influence PEU before direct hands-on experience with a system. However, the relationship became significant after the experience. In a more recent study on the determinants of PEU, Venkatesh (2000) found a similar relationship between OU and PEU. Note that, as indicated by Venkatesh and Davis (1996), OU essentially measures the objective ease of learning of a system by using comparative performance as the surrogate. The above empirical findings on the relationship between OU and PEU suggest that PEU relates to performance only after direct hands-on experience, i.e., when PEU is adjusted by the experience.

Besides the literature on the TAM, empirical studies on self-efficacy also support our explanation. Many studies have reported significant correlation between self-efficacy and task performance (e.g., Bandura, 1982). However, other studies found the relationship between self-efficacy and performance was not very strong (e.g., Locke et al., 1984; Stumpf et al., 1987; Taylor et al., 1984; Wood & Locke, 1987). In order to make sense of the conflicting findings, Gist and Mitchell (1992) explained that the lack of direct experience with a task along with task complexity and feedback ambiguity could degrade the efficacy-performance relationship. Because self-efficacy and PEU are two highly correlated constructs (see Igbaria & Iivari, 1995; Venkatesh & Davis, 1996), we believe the same explanation by Gist and Mitchell (1992) also applies to the relationship between PEU and performance. Thus, the differentiation between PEL and PEU of the OOM has lead us to conclude that ease of learning and ease of use, even though are similar constructs, do not go along with each other when dealing with a technology such as the object-oriented one.

Limitations and Implications for Future Research

The limitations of our study center around external validity and the design of the experimental task. Some concerns arise due to the use of students in research of this nature. However, the use of business students in a lab setting enabled us to control previous experience in structural methodologies that, otherwise, would be very difficult to control. In addition, although the subjects were not randomly selected, we carefully controlled certain parameters such as their maturity, prior experience, field of studies, and others so that the sample was not biased toward any particular direction.

Agarwal et al. (1996a, 1996b) suggested that some tasks are more process-oriented while some others are more object-oriented depending on the degree of process and structure inherent in the task. This suggests that the nature of the problem can potentially influence not only the performance of applying the OOM but also the perceptions about ease of learning and use of the OOM given the different types of subjects' previous experience. Even though we made an attempt to create a problem that combines both processes and structure features, no formal method was utilized to actually test the degree of process and structure inherent in the designed task. The process of designing the problem was a subjective assessment that may have a chance of misclassification. However, the high reliability shown by the two raters and the objective classification schema in the key solution helped address this limitation.

The experimental results of this study suggest some interesting directions for future research. First, a further study using the TAM could be carried out in order to determine systems analysts intention to adopt the OOM. No research, as far as we know, has been conducted to understand the usage behavior of systems analysts in adopting design methodologies by applying the TAM. Even though Johnson et al. (1999) made an attempt to determine developer beliefs about object-oriented systems, they based their analysis on the theory of planned behavior (Ajzen, 1991).

Second, the uniqueness of this study considering PEL and PEU as two different constructs generates many opportunities for future research. In order to corroborate the results of this study and to create a broader, cumulative knowledge of the perceptions of learning and using the OOM considering previous experience in traditional systems, it would be desirable to reproduce this research. As Adams et al. (1992) pointed out "the tendency of IS researchers to become complacent or discouraged with progress in a specific area after conducting what would be considered a limited number of studies in other domains should be challenged. We should begin to focus on replication, refinement, and development of models and measures" (p.245). The replication could incorporate different items for the latent variables so that a similar competitive model could be tested.

Finally, in order to explain the paradoxical findings on the effects of PEL and PEU on performance, we proposed a theory that the perception of ease of learning or ease of use influences performance only when it is adjusted based on direct experience. If this theory is true, our results imply that, in order to make PEL and PEU to be more predictive of task performance, users must be offered opportunities to grow sufficient direct experience with a technology. The items that measure PEL and PEU must be pertinent to specific tasks rather cross-domain or general-domain tasks. By doing so, PEL and PEU will be more reflective of experience and objective usability. Of course, more research is needed in order to validate our explanation as well as those implications.

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Appendix: Experimental Task

A hardware store has decided to design a point-of-sale system and hired you to capture their data and process requirements. The store carries many different types of products, including tools, and garden supplies. At first, you thought a simple sales system would work for this company. After all, each item has a cost, a description, an inventory level, and a list price. But after talking with the managers, you quickly learned that products are grouped by category (garden supplies and tools) and their items have important differences:

- The tools have warranties, but the garden supplies do not. In addition, certain electric tool requires a license number to be sold.

- All garden products have a temperature constraint—some plants have to be moved inside if the temperature drops below a certain level.

- The store keeps data about its customers including their customer numbers, names, phone numbers, and addresses. Some registered customer can negotiate for a discount. Each time when a customer makes a purchase, his phone number is used to retrieve his data including his discount rate. His phone number can be also used to retrieve his past purchases.

When clerks ring up an item, the system will retrieve the item description and the list price and compute the sub-total. At the end of the transaction, the system computes the total charge. Note that when clerks check out certain garden-used chemicals, they are supposed to get the Federal Pesticide License number (FPLNO) from the customer.

The store orders its supplies from many suppliers, each one grants the company a different level of discounts along with an authorization number. Some require the use of electronic data interchange (EDI) to get the best discount.

When managers order an item, they must identify the suppliers who sell the item. Then they select a supplier who provides the best deal, and follows the rules specified by that supplier to make an order. If a certain electrical tool is ordered, the corresponding license number must be submitted to the supplier.